

WEIGHTED MYRIAD FILTERATIVE REGRESSED GRADIENT DESCENT STACKED ENSEMBLE CLASSIFICATION FOR PLANT LEAF DISEASE DETECTION

M. Sheela Newsheeba

Research Scholar, Department of Computer Science, Sri Jayendra Saraswathy Maha
Vidyalaya College of Arts & Science, Coimbatore-641005, Tamil Nadu, India
Email: sheela79.rincy@gmail.com

Dr. N. Umadevi

Head & Associate Professor, Department of Computer Science & IT, Sri Jayendra
Saraswathy Maha Vidyalaya College of Arts & Science, Coimbatore-641005, Tamil Nadu,
India

Abstract: Plant leaf disease detection utilizing advanced learning methods can minimize significant losses in quantity and quality of crop production. However, the current detection methods have drawbacks in handling noisy and blurred images for accurate plant disease detection. A novel Weighted Myriad Filterative Regressed Gradient Descent Stacked Ensemble Classification (WMFRGDSEC) method has been developed to overcome the existing limitations and provide accurate detection. In this method, the initial pre-processing is performed on the collected wheat leaf images to eliminate noise and image enhancement using the Weighted Myriad filtering technique. Then, the image regions are segmented using Prevosti's concordance correlative Range segmentation, and the features are extracted by the Kriging regression technique to reduce the detection time. Finally, the accurate classification is done using a Gradient Descent stacked ensemble classifier through several weak learners. Evaluated over 4000 public wheat leaf images from LWDCD2020 dataset, this WMFRGDSEC method increased the disease detection accuracy to 90.7% with a reduced false-positive rate of 8.2% and a detection time of 61.11 seconds.

Keywords: Plant Leaf Disease Identification, Weighted Myriad Filtering, Prevosti's concordance correlative Range segmentation, Kriging regression, Gradient Descent stacked ensemble classifier.

Introduction

Plant diseases are the major threats to efficient food yield and might create significant losses to the farmers and food safety concerns. Therefore, early plant disease identification is essential for precision agriculture [1]. Many complexities exist in monitoring the disease occurring in the plants, such as practical constraints, time limitations, etc. The utilization of Computer vision techniques and image processing methods for detecting plant leaf diseases has been an efficient strategy for detecting plant diseases from leaf images [2].

Several machine learning (ML) and deep learning (DL) techniques were recently used for automatically detecting and categorizing the diseases of plants utilizing its leaf images with

high accuracy [3]. These methods can effectively analyze the diseased plants and crop regions to reduce crop damage and increase yields. Different ML models, such as K-means, Decision Trees (DT), support vector machines (SVM), Artificial Neural Networks (ANN), etc., are used for identifying diseases related to plants. The diverse methods of ML and DL have more significant advantages over the other methods. Still, these methods are also affected by several challenges which might affect the overall detection accuracy and model efficiency [4]. The challenges are explained as follows. Time complexity is the main challenge while using DL and ML approaches, and the plant disease detection technologies are outdated, as it uses past data for diagnosis. Next, segmentation sensitivity highly affects the disease detection model, i.e., the Region of Interest (RoI) produces the required accuracy only when it has a high sensitivity and accuracy level. In addition, complexity arises when there are no adequate resources to support the application of technologies. The ML and DL model requires many resources to implement disease detection technology in plants and humans. This affects the success of research and technology implementation [5].

The significant issues in plant leaf disease detection are overcome by introducing a novel WMFRGDSEC. The novel contribution is the practical WMFRGDSEC approach introduced to improve plant-leaf disease identification accuracy based on pre-processing, segmentation, feature extraction, and classification. The first novel method is an efficient pre-processing model called the Weighted Myriad filtering technique, which removes the noise pixels to improve the quality of the image. This method enhances the peak signal-to-noise ratio by minimizing the mean square error value. A Prevosti's concordance correlative Range segmentation is applied to segment the input image into different parts for extracting the region of interest. Kriging regression is used for texture feature extraction from the input leaf image. The Normalized Freeman chain code histogram is also applied for extracting the shape feature. Then, the color feature is extracted for accurate classification with minimum time consumption. The second novel method is the Gradient Descent stacked ensemble classifier, which is applied to enhance plant-leaf disease Identification accuracy and reduce the false positive rate. A sequence of experiments was conducted to measure the quantitative and qualitative performance analysis of the proposed WMFRGDSEC technique along with conventional methods based on different performance metrics.

The paper is arranged as follows: Section 2 briefly describes the recent literature studies. Section 3 describes the proposed WMFRGDSEC methodology for leaf disease detection. Section 4 presents the qualitative and quantitative analyses utilizing different parameters. Finally, section 5 provides the conclusion.

Related Works

Recent studies have utilized ML, and DL methods for plant leaf diseases as their efficiency was better than the traditional methods. Some of the most prominent studies are discussed in this section. Bao et al. [6] proposed Elliptic Maximum Margin Criterion (E-MMC) metric learning approach with a gradient ascent algorithm (GAA) to find the wheat leaf diseases along with their severities. This method utilized GAA to optimize the E-MMC classifier. Finally, the severity of stripe rust and powdery mildew of wheat is detected with an accuracy of 93.33% for the wheat leaf disease dataset. Bao et al. [7] also developed a lightweight convolutional neural network called SimpleNet to detect wheat ear disease. This method used the

Convolutional Block Attention mechanism (CBAM) and feature fusion model to enhance the glume blotch and scab wheat-ear diseases detection accuracy to 94.1%. But, this model has data limitations problems since the data contains only the winter wheat ear images and not the summer wheat images due to the limited symptoms' learning. Hayit et al. [8] identified yellow rust disease in wheat images using convolutional neural networks (CNN). In this method, the transfer learning model is trained on a large dataset, and the Yellow-Rust-Xception CNN model was built to increase the test accuracy to 91%. Goyal et al. [9] also utilized CNN to classify the Leaf and spike wheat diseases of 10 different classes with 97.88% test accuracy and 98.62% training accuracy on the Large Wheat Disease Classification (LWDCD2020) Dataset. However, this CNN model has also increased the computation complexity.

Wójtowicz et al. [10] identified wheat and rye leaf diseases from spectral images using Random Forest (RF) classifier. The spectral vegetation indices are extracted and selectively fed to the RF classifier to obtain accuracies of 91.7% and 96.6% for wheat and rye diseases, respectively. However, RF provided a high false alarm rate for some spectral images. Khan et al. [11] detected the powdery mildew wheat disease and its severity utilizing Partial Least Squares regression based Linear Discriminant Analysis (PLS-LDA). This model extracted the vegetation indices (VIs) to achieve resultant accuracy of 82.35%. However, the results were obtained with leaves on limited scales and might be inadequate for a definitive conclusion. Kaur et al. [12] presented a hybrid EfficientNet CNN with a transfer learning (TL) model to explore the plant diseases in grapevines using feature reduction by the Logistic Regression approach. This model obtained an accuracy of 98.7% on the Plant Village dataset, but this model has a higher training time due to poor tuning of the CNN model parameters. Jiang et al. [13] recognized the rice and wheat leaf diseases using an enhanced Visual Geometry Group Network-16 (VGG16) model based on multi-task deep transfer learning. In this model, ImageNet pre-trained model is utilized for transfer learning and alternate learning of VGG16. This model provided accuracies of 97.22% and 98.75%, respectively, for rice and wheat leaf diseases. Yet, this model does not consider the impact of inference factors in the images. Shrivastava and Pradhan [14] suggested an SVM model to detect rice plant diseases and achieved 94.65% accuracy. However, this approach was practical only for binary class images. Chen et al. [15] implemented the prediction of rice plant disease using the DenseNet-Inception module-based deep transfer learning model. This method is evaluated on a public dataset and obtained an accuracy of 94.07% for binary classification and 98.63% accuracy for multi-class classification. The only limitation is that this model fails to identify multiple diseases in the same image. Pham et al. [16] implemented mango leaves classification using ANN and Adaptive Particle-Grey Wolf Optimization (APGWO) based feature selection. This approach attained an accuracy of 89.41% with reduced model complexity. However, this method identified powdery mildew disease with reduced accuracy than the other diseases. Chen et al. [17] developed a tomato-leaf disease prediction model using AlexNet CNN and obtained an accuracy of 98% with a loss rate of 0.1331. However, the training process is relatively slow in AlexNet compared to the other CNN architectures. Yogeshwari and Thailambal [18] employed DCNN for plant leaf disease detection. In this approach, the segmentation process is carried out using Fast Fuzzy C Means Clustering (IFFCMC) and Adaptive Otsu (AO) thresholding approaches. Then, the features were extracted using GLCM and dimensionality was reduced

by PCA. This DCNN classifier achieved an accuracy of 97.43%. However, this method has increased the model's complexity.

Guo et al. [19] identified the Plant disease based on Region Proposal Network (RPN) based transfer learning. This method obtained an accuracy of 83.57%, but it requires more training time as Chan–Vese segmentation algorithm needs more iterative computations. Liu et al. [20] recognized the Plant disease using Long Short Term Memory (LSTM) with three reweighting approaches to improve feature learning. This method obtained a test accuracy of 99.78% for the Plant Village dataset, but it suffers from poor handling of the class imbalance problem and is relatively slow in processing. Barburiceanu et al. [21] used CNNs for feature extraction and SVM classifiers for detecting plant diseases. This method is evaluated on the Plant Village dataset and obtained an accuracy of 80.2% with an extraction time of 117.62s. However, this method requires a longer training time. Albattah et al. [22] presented a customized CenterNet model with DenseNet-77 to predict and classify the plant diseases of the Plant Village dataset with an accuracy of 99.98%. But this model also has poor convergence speed.

From the literature, the significant problems identified for leaf disease detection methods are that handling noisy and blurred images reduces the detection rate. Also, many methods' processing and training times were higher due to their complex architecture and slow feature learning capabilities. This study considers these limitations, and an efficient approach is presented for accurate plant leaf disease detection.

Proposed WMFRGDSEC Methodology

The proposed WMFRGDSEC technique consists of four major stages: image collection, pre-processing, feature extraction, and classification. The wheat leaf images collected from the LWDCD2020 dataset [23] are used to evaluate this plant-leaf disease detection approach. A detailed block diagram of the proposed leaf disease classification method using WMFRGDSEC is illustrated in Figure 1.

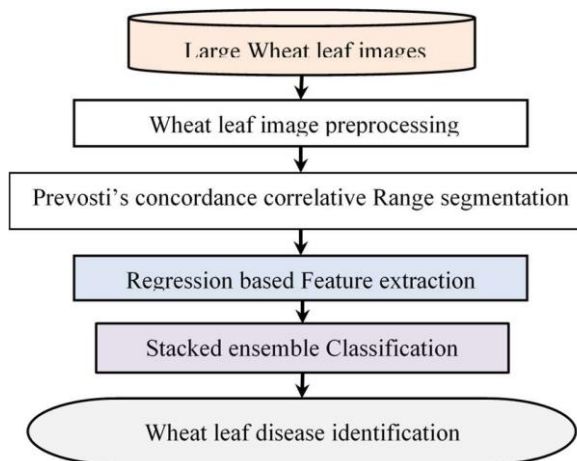


Figure. 1 Block diagram of the proposed WMFRGDSEC technique

Figure 1 illustrates the block diagram of the proposed WMFRGDSEC method, which incorporates five steps. This method applies the pre-processing procedure to leaf disease images using the Weighted Myriad filtering technique. Third, Prevosti's concordance correlative Range segmentation is performed to partition the image into several segments to

identify the disease in a limited time. Feature extraction is performed on pre-processed images. With the extracted features, the Gradient Descent stacked ensemble classifier identifies the disease with decreased error rate.

Weighted Myriad Filtering based image pre-processing

The proposed WMFRGDSEC technique performs pre-processing as the first step to remove the noise by estimating the maximum likelihood location for identifying the noisy pixels.

Let $I_1, I_2, I_3, \dots, I_n$ denotes the images of plant-leaf from the plant-leaf disease dataset. The pixels $p_1, p_2, p_3, \dots, p_m$ of the input images are arranged in the filtering kernel window in the input image. After the pixel arrangement, the center pixel is selected for noise removal. The Weighted Myriad Filtering is applied to the window and computes the maximum likelihood location estimation between the center and neighboring pixels.

$$\varphi_f = \arg \max(\vartheta * |p_{ij} - p_n|) \quad (1)$$

Here, φ_f denotes a filtered output, $\arg \max$ indicates an argument of the maximum function, p_{ij} denotes a center pixel and p_n indicates a neighboring pixel, ϑ indicates a weight. The weight function helps to control the blurring of the image. From Eq. (1), a pixel with the maximum possibility of neighboring pixels deviating from the center pixel is identified as noisy. These identified noisy pixels are eliminated from the window, which enhances the input image quality. Algorithm 1 summarizes the Weighted Myriad Filtering technique.

Algorithm 1: Weighted Myriad Filtering based image pre-processing

Input: Image dataset ‘D’ number of images ‘ $I_1, I_2, I_3, \dots, I_n$ ’

Output: Enhance the image quality

Collect images $I_1, I_2, I_3, \dots, I_n$ from dataset

For each image I_i

Arrange the pixels in the kernel window in the form of rows and column

Sort the pixels $p_1, p_2, p_3, \dots, p_m$

Take the center value p_{ij}

Find maximum likelihood

Identify the noisy pixels from the filtering window

Return (quality improved plant leaf image)

End for

Algorithm 1 illustrates the steps involved in the noise removal procedure. The input images are given to the pre-processing step using Weighted Myriad Filtering, which discards the noise artifacts and improves the image quality. The pixels of leaf images are organized in the kernel window as rows and columns, and it takes the center value as the reference value. The noisy pixels are determined based on the maximum likelihood between the center and neighboring pixels. The pixel that deviates from the center pixels is called a noisy pixel. This process enhances the PSNR and minimizes the error rate.

Prevosti’s concordance correlative Range segmentation

Image segmentation helps to improve disease detection with minimum time consumption. Therefore, the proposed technique uses Prevosti’s concordance correlative Range segmentation. The proposed segmentation is the task of segmenting a range of images containing depth information for each pixel so that similar pixels of the same surface belong to

the same region with no overlap between the distinct regions. The combination of these regions creates the whole image.

Prevosti's concordance correlation coefficient measures the relationship between two variables (i.e., pixels). Let us consider the pixels in the form of rows (i) and columns (j).

$$p_{ij} = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1n} \\ p_{21} & p_{22} & \dots & p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ p_{m1} & p_{m2} & p_{m2} & p_{mn} \end{bmatrix} \quad (2)$$

After arranging the pixels, the concordance correlation between the pixels is measured as,

$$\varphi = \frac{2 * p_i p_j}{p_i^2 + p_j^2 + D_{ij}} \quad (3)$$

$$D_{ij} = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^m |p_i - p_j| \quad (4)$$

Where φ indicates a concordance correlation between the pixels, D_{ij} denotes a Prevosti's distance between the two pixels p_i, p_j and n indicates the number of pixels. Lin's Concordance Correlation coefficient provides the results from 0 to 1. The different segmented regions are obtained and the region of interest, i.e., the infected area, is identified based on correlation coefficient values.

Feature extraction

Feature extraction separates the visual information from the pre-processed image. The proposed WMFRGDSEC technique uses the Kriging regression for extracting the different texture features and the Normalized Freeman chain code histogram for shape feature extraction. Followed by color feature extraction is performed for different representations of the image.

Kriging regression-based texture feature extraction

Kriging regression is a machine learning technique based on the Gaussian process directed by prior covariance. It provides information about the spatial representation of colors or intensities.

$$R_K = \exp\left(\frac{|p_i - \mu|}{2d^2}\right) \quad (5)$$

Where, R_K indicates a Kriging regression function, p_i indicates a pixel i-th value, μ denotes a mean of the pixels, d indicates a deviation, and exp denotes an exponential function.

Normalized Freeman chain code histogram-based Shape feature extraction

Normalized Freeman chain code histogram identifies the different directions to reveal the shape of the object boundary. It works in two ways, either 4-connected or 8-connected neighborhood pixels. In this work, the 8-connected neighborhood pixels method is implemented for forming the chain code to find the object boundary.

Let us consider the image pixels are $p_1, p_2, p_2, \dots, p_m$, and apply the shape feature extraction technique to define the object's contour. Figures 2(a) and (b) show an 8-connected neighborhood pixels method based on a normalized Freeman chain code histogram.

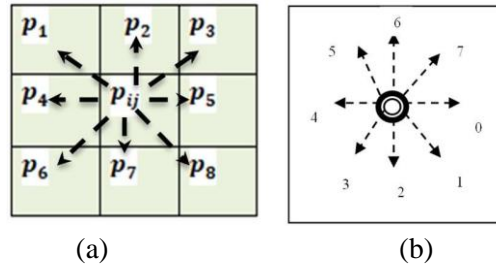


Figure. 2 (a) 8-connected neighborhood pixels method (b) normalized Freeman chain code histogram

Initially, the chain coding's starting point is circled and directed to work in a clockwise direction. It noted that even to obtain a variable number of neighborhood pixels. As shown in figure 2, the beginning point of chain coding is denoted with a black circle, and its direction is clockwise. The obtained direction of the code is 01245, and the object boundary is marked as the direction with the orange color. In this way, the shape features of the object are extracted.

Color feature extraction

Finally, the proposed technique performs the color feature-extracting procedure. For accurate disease identification, color is considered a significant feature. The proposed method manipulates the colors of the original image in RGB (red, color, blue) and is converted into HSV (hue, saturation, value).

$$C_H = \cos^{-1} \left[\frac{1}{2} * \frac{[(r-g)+(r-b)]}{\sqrt{(r-g)^2+(r-g)(g-b)}} \right] \quad (6)$$

$$C_S = 1 - 3 * \frac{1}{(r+g+b)} [arg \min(r, g, b)] \quad (7)$$

$$C_V = \frac{1}{3} * [(r + g + b)] \quad (8)$$

By using (6), (7), and (8), the color features are extracted. The feature extraction process used in the WMFRGDSEC technique reduces the time taken to identify the leaf disease.

Gradient Descent Stacked Generalization based plant leaf disease identification

Gradient Descent Stacked Generalization (GDSDG) is an ensemble machine learning algorithm. The main advantage of Stacked Generalization is to improve the disease identification accuracy than the boosting and bagging ensemble classifier. This model considers the training feature, i.e., extracted feature (F_E) as input. The Stacked Generalized ensemble approach initially builds different weak learners, such as KNN, SVM, and Decision tree (DT). Their results are combined to obtain a robust classifier with reduced error.

KNN: Let us consider the training feature (i.e., extracted feature) is F_E , and the testing disease feature is denoted as F_d . KNN classifier is based on the Minkowski distance measure between the extracted features and disease features. Therefore, the Minkowski distance is measured as given below,

$$D = arg \min (\sum |F_E - F_d|^n)^{1/n} \quad (9)$$

Here D indicates a distance, F_E indicates Extracted features, F_d indicates a disease feature with the distance of order 'n' (where n is an integer), $arg\ min$ denotes an argument of the minimum function. If the distance is minimal between the Extracted features and Disease features, then the image is classified as a disease-affected image; else, it is classified as normal.

SVM: SVM uses an optimal hyper plane for classifying the images based on kernel similarity. The optimal hyper plane is the decision boundary between the two classes $\{+1,-1\}$. The decision boundary is expressed as follows,

$$h \rightarrow w.F_E + d = 0 \quad (10)$$

Here h symbolizes a decision boundary, w denotes the normal weight vector to training samples (i.e. F_E), ' d ' represents a bias. The two marginal hyper planes are formed on the boundary's lower or upper side.

$$B_1 = w.F_E + d \times \theta \quad (11)$$

$$B_2 = w.F_E - d \times \theta \quad (12)$$

Here, B_1, B_2 are the marginal hyper planes for classifying the plant-leaf images into either the lower or upper side of the boundary, and θ denoting the altering angle.

$$K = sign \sum w_i B_i \varphi (F_E, F_d) \quad (13)$$

In Eq. (13), K denotes predicted classification results, w_i denotes weights, B_i indicates dependent variable (i.e., output), $\varphi (F_E, F_d)$ indicates similarity between the features, and $sign$ represents positive (+1) or negative (-1). The hyper plane analyzes the two features and returns the output '+1' and '-1'. Here, '+1' indicates the disease-affected image and '-1' indicates the normal image.

Decision tree: DT contains one root node linked with the leaf nodes. The disease features are decided from the extracted features by the root nodes. The leaf node provides further classification outcome whether it is affected or normal leaf image. The root node measures the similarity between extracted and disease features using Morisita-Horn's index to determine the images as normal or disease based on the similarity value.

$$S = 2 * \left[\frac{\sum F_E * F_d}{\sum F_E^2 + \sum F_d^2} \right] \quad (14)$$

From Eq. (14), Morisita-Horn's index S is measured based on the summation of the product of paired score of two features $\sum F_E * F_d$, the squared score of the feature F_E is $\sum F_E^2$ and a squared score of feature F_d is $\sum F_d^2$. Morisita-Horn's index provides an output value between 0 and 1.

$$S = \begin{cases} +1, & \text{Disease} \\ 0, & \text{normal} \end{cases} \quad (15)$$

The value of ' $S = +1$ ' indicates that the features are similar and plant-leaf disease is identified, whereas the value of '0' indicates the classification result of the plant-leaf image as normal.

The weak learners are combined and measured the out-of-sample error as the difference between the expected and predicted errors.

$$E_r = \{E_x - E_p\} \quad (16)$$

In Eq. (16), E_r denotes the amount of sample error, E_x is the expected error, E_p symbolizes the predicted error. The results with a minimum error are identified by applying the gradient descent function.

$$Y = \underset{r}{\operatorname{arg\,min}} E (Z) \quad (17)$$

In Eq. (17), Y represents the strong classification results, *arg min* denotes an argument of a minimum function, which is used to find the minimum error (E_r) of weak learners as strong classification results. The process involved in the proposed ensemble classification is summarized in Algorithm 2.

Algorithm 2: Gradient descent stacked ensemble classification

Input: Extracted features F_E and disease feature F_d

Output: Improve the disease identification accuracy

Begin

For the extracted features F_E and disease feature F_d

Construct ‘k’ weak learners

//Apply KNN classier

Measure distance between F_E and F_d

If (*arg min* D') then

Image is classified as a disease

Else

The image is classified as normal.

End if

//Apply SVM classier

Construct optimal hyper plane h .

Find two marginal hyper planes B_1, B_2

Measure the similarity between the features

If ($K = +1$), then

Image is classified as a disease

Else if ($K = -1$), then

Image is classified as a disease

End if

//Apply decision tree

Measure the similarity between F_E and F_d

If ($S = +1$), then

Image is classified as a disease

Else

Image is classified as ‘normal’

End if

Combine all of the weak learners $Y = \sum_{i=1}^m w_i$

For each w_i

Measure error E_r

Find the weak classifier with minimum error





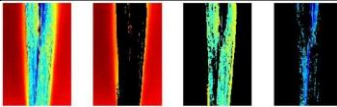
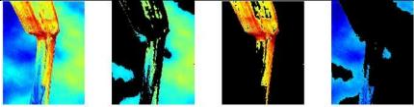
```

Return (strong classification results)
End for
End for
End
    
```

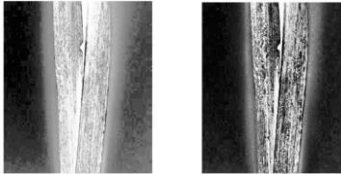
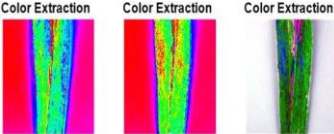
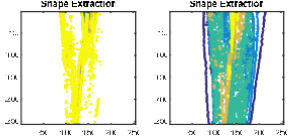
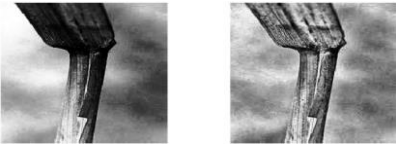
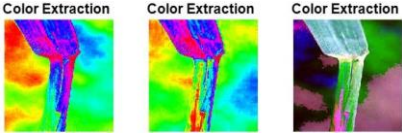
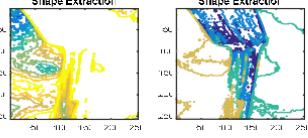
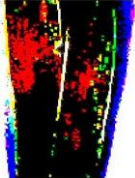

Algorithm 2 illustrates the steps of the Gradient descent stacked ensemble classification method constructed using KNN, SVM and decision tree for predicting the plant leaf disease. The accurate classification result is obtained by combining the outcome of weak classifiers, and each classifier’s training error is estimated. The resulting robust classifier provides results with a reduced error rate.

The qualitative performance analysis is performed to show the visual representation. The qualitative output analysis of the WMFRGDSEC for each stage of the proposed approach is shown in Table 1.

Table 1. Step-by-step Qualitative analysis of the WMFRGDSEC technique

Processes	Diseased Input Image	Healthy Input Image
Input images		
Weighted Myriad filtering-based image pre-processing		
Prevosti’s concordance correlative Range segmentation		

WEIGHTED MYRIAD FILTERATIVE REGRESSED GRADIENT DESCENT STACKED ENSEMBLE
CLASSIFICATION FOR PLANT LEAF DISEASE DETECTION

<p style="text-align: center;">Feature extraction</p>	<div style="text-align: center;">  <p>Texture feature extraction</p> </div> <div style="text-align: center;">  <p>color feature extraction</p> </div> <div style="text-align: center;">  <p>shape feature extraction</p> </div>	<div style="text-align: center;">  <p>Texture feature extraction</p> </div> <div style="text-align: center;">  <p>color feature extraction</p> </div> <div style="text-align: center;">  <p>shape feature extraction</p> </div>
<p style="text-align: center;">Gradient Descent Stacked Ensemble Classification</p>	<div style="text-align: center;">  <p>Disease</p> </div>	<div style="text-align: center;">  <p>Healthy</p> </div>

Experimental Results and Discussion

Experiments are conducted for the proposed WMFRGDSEC approach in MATLAB using the LWDCD2020 dataset [23]. LWDCD2020 has included three wheat leaf disease images and normal images, totaling 4,500 images with four classes: one healthy wheat and three disease classes, namely root rot and crown, loose smut and Leaf Rust images. For evaluation, 4000 images are considered totally in healthy and diseased classes. All three diseased classes are combined into a single diseased class.

The quantitative performance analysis uses parameters, namely disease detection accuracy, False-Positive Rate (FPR), disease detection time, and Peak Signal-to-Noise Ratio (PSNR).

Table 2 shows the output values obtained for the proposed WMFRGDSEC technique in the quantitative analysis for different numbers of input images in 10 iterations.

Table 2. Performance of WMFRGDSEC

Number of images	Average accuracy (%)	FPR (%)	Detection time (seconds)	PSNR (dB)
400	90	9	43	62.45
800	91	7	46	63.53
1200	90	9	49	65.45
1600	91	8	54	68.52
2000	92	7	60	72.33
2400	90	9	62	74.58
2800	91	8	67	76.85
3200	90	9	74	78.55
3600	92	8	76	81.25
4000	90	8	80	63.52

Table 2 shows that the proposed WMFRGDSEC technique performs better for the LWDCD2020 dataset with an average accuracy of 90.7%, FPR of 8.2%, detection time of 61.11 seconds, and PSNR value of 70.7dB for the 10 iterations.

To further evaluate the superiority of the proposed technique, the performance of WMFRGDSEC is compared with the existing methods in the literature from Section 2. For a fair comparison, the existing methods are also implemented in MATLAB under the same environment conditions using the 4000 images from the LWDCD2020 dataset [23]. The evaluations are performed for 10 iterations with a different number of input images in each iteration, and the average results are presented for comparison. Table 3 shows the comparison results as average values obtained for each method over the 10 iterations.

Table 3. Comparison results

Methods	Average accuracy (%)	FPR (%)	Detection time (seconds)	PSNR (dB)
E-MMC [6]	87.56	11.6	83.65	62.38

WEIGHTED MYRIAD FILTERATIVE REGRESSED GRADIENT DESCENT STACKED ENSEMBLE
CLASSIFICATION FOR PLANT LEAF DISEASE DETECTION

SimpleNet [7]	88.17	10.4	67.95	66.67
CNN [8, 9]	88.01	10.8	70.27	65.95
RF [10]	87.26	11.9	80.91	63.39
PLS-LDA [11]	86.61	12.6	81.25	61.25
EfficientNet [12]	88.35	10.6	70.34	68.51
VGG16 [13]	88.02	10.7	69.96	68.86
SVM [14]	87.69	11.2	79.65	66.87
DenseNet-Inception [15]	89.78	9.3	66.45	67.98
ANN [16]	87.88	11.5	69.88	60.55
AlexNet [17]	88.5	10.5	68.37	65.03
DCNN [18]	88.05	10.8	67.18	64.76
RPN [19]	87.67	11.8	80.32	56.45
LSTM [20]	89.25	9.88	65.98	66.78
CNN-SVM [21]	89.75	9.67	68.88	61.47
CenterNet [22]	88.98	10.4	72.65	65.65
Proposed WMFRGDSEC	90.7	8.2	61.11	70.70

The comparison results in Table 3 show that the proposed WMFRGDSEC technique has provided significantly better performance than the existing methods from the literature. It has outperformed the existing methods by 1% to 4% higher accuracy, 0.3% to 4% lesser FPR, 4 to 20 seconds lesser detection time and 2-14dB reduced PSNR.

The proposed WMFRGDSEC has achieved 90.7% disease detection accuracy which is 1.72%, 1%, 1.5%, 3.03%, 2.65%, 2.2%, 2.82%, 0.92%, 3%, 2.68%, 2.35%, 4.09%, 3.44%, 2.69%, 2.53% and 3.14% higher than the compared existing methods. This significant improvement is attributed to the efficient pre-processing by Weighted Myriad filtering has reduced the time complexity in computations and improved the classification accuracy of the novel Gradient descent stacked ensemble classifier with less time consumption.

Conclusion

WMFRGDSEC technique is developed in this paper to classify and identify wheat leaf diseases using the GDSG ensemble classifier. The simulation is conducted with the LWDCD2020

dataset, and the quantitative analysis is derived in terms of PSNR, accuracy, FPR and detection time. The comparative results are also provided against the existing methods. The observations have concluded that the proposed WMFRGDSEC technique has achieved an average accuracy of 90.7%, FPR of 8.2%, detection time of 61.11 seconds, and PSNR value of 70.7dB which are 1% to 4% higher accuracy, 0.3% to 4% lesser FPR, 4 to 20 seconds lesser detection time and 2-14dB reduced PSNR than the existing methods. Although efficient results are obtained, investigations can be conducted to reduce the overall training time. Also, the possibility of applying the proposed technique for diverse plant leaf images will be examined in the future.

References

R. Akhter, and S. A. Sofi, "Precision agriculture using IoT data analytics and machine learning", *Journal of King Saud University-Computer and Information Sciences*, Vol. 34, No. 8, pp. 5602-5618, 2022.

D. I. Patrício, and R. Rieder, "Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review", *Computers and electronics in agriculture*, Vol. 153, No. 1, pp. 69-81, 2018.

J. A. Wani, S. Sharma, M. Muzamil, S. Ahmed, S. Sharma, and S. Singh, "Machine learning and deep learning based computational techniques in automatic agricultural diseases detection: Methodologies, applications, and challenges", *Archives of Computational Methods in Engineering*, Vol. 29, No. 1, pp. 641-677, 2022.

R. Sujatha, J. M. Chatterjee, N. Z. Jhanjhi, and S. N. Brohi, "Performance of deep learning vs machine learning in plant leaf disease detection", *Microprocessors and Microsystems*, Vol. 80, No. 1, pp. 103615, 2021.

R. I. Hasan, S. M. Yusuf, and L. Alzubaidi, "Review of the state of the art of deep learning for plant diseases: a broad analysis and discussion", *Plants*, Vol. 9, No. 10, pp. 1302, 2020.

W. Bao, J. Zhao, G. Hu, D. Zhang, L. Huang, and D. Liang, "Identification of wheat leaf diseases and their severity based on elliptical-maximum margin criterion metric learning", *Sustainable Computing: Informatics and Systems*, Vol. 30, No. 1, pp. 100526, 2021.

W. Bao, X. Yang, D. Liang, G. Hu, and X. Yang, "Lightweight convolutional neural network model for field wheat ear disease identification", *Computers and Electronics in Agriculture*, Vol. 189, No. 1, pp. 106367, 2021.

T. Hayit, H. Erbay, F. Varçın, F. Hayit, and N. Akci, "Determination of the severity level of yellow rust disease in wheat by using convolutional neural networks", *Journal of Plant Pathology*, Vol. 103, No. 3, pp. 923-934, 2021.

L. Goyal, C. M. Sharma, A. Singh, and P. K. Singh, "Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture", *Informatics in Medicine Unlocked*, Vol. 25, No. 1, pp. 100642, 2021.

A. Wójtowicz, J. Piekarczyk, B. Czernecki, and H. Ratajkiewicz, "A random forest model for the classification of wheat and rye leaf rust symptoms based on pure spectra at leaf scale", *Journal of Photochemistry and Photobiology B: Biology*, Vol. 223, No. 1, pp. 112278, 2021.

I. H. Khan, H. Liu, W. Li, A. Cao, X. Wang, H. Liu, and X. Yao, “Early detection of powdery mildew disease and accurate quantification of its severity using hyperspectral images in wheat”, *Remote Sensing*, Vol. 13, No. 18, pp. 3612, 2021.

P. Kaur, S. Harnal, R. Tiwari, S. Upadhyay, S. Bhatia, A. Mashat, and A. M. Alabdali, “Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction”, *Sensors*, Vol. 22, No. 2, pp. 575, 2022.

Z. Jiang, Z. Dong, W. Jiang, and Y. Yang, “Recognition of rice leaf diseases and wheat leaf diseases based on multi-task deep transfer learning”, *Computers and Electronics in Agriculture*, Vol. 186, No. 1, pp. 106184, 2021.

V. K. Shrivastava, and M. K. Pradhan, “Rice plant disease classification using color features: a machine learning paradigm”, *Journal of Plant Pathology*, Vol. 103, No. 1, pp. 17-26, 2021.

J. Chen, D. Zhang, Y. A. Nanekaran, and D. Li, “Detection of rice plant diseases based on deep transfer learning”, *Journal of the Science of Food and Agriculture*, Vol. 100, No. 7, pp. 3246-3256, 2020.

T. N. Pham, L. Van Tran, and S. V. T. Dao, “Early disease classification of mango leaves using feed-forward neural network and hybrid metaheuristic feature selection”, *IEEE Access*, Vol. 8, No. 1, pp. 189960-189973, 2020.

H. C. Chen, A. M. Widodo, A. Wisnujati, M. Rahaman, J. C. W. Lin, L. Chen, and C. E. Weng, “AlexNet convolutional neural network for disease detection and classification of tomato leaf”, *Electronics*, Vol. 11, No. 6, pp. 951, 2022.

M. Yogeshwari, and G. Thailambal, “Automatic feature extraction and detection of plant leaf disease using GLCM features and convolutional neural networks”, *Materials Today: Proceedings*. In Press, pp. 1-7, 2021.

Y. Guo, J. Zhang, C. Yin, X. Hu, Y. Zou, Z. Xue, and W. Wang, “Plant disease identification based on deep learning algorithm in smart farming”, *Discrete Dynamics in Nature and Society*, Vol., 2020, No. 1, pp. 1-11, 2020.

X. Liu, W., Min, S. Mei, L. Wang, and S. Jiang, “Plant disease recognition: A large-scale benchmark dataset and a visual region and loss reweighting approach”, *IEEE Transactions on Image Processing*, Vol. 30, No. 1, pp. 2003-2015, 2021.

S. Barburiceanu, S. Meza, B. Orza, R. Malutan, and R. Terebes, “Convolutional Neural Networks for Texture Feature Extraction. Applications to Leaf Disease Classification in Precision Agriculture”, *IEEE Access*, Vol. 9, No. 1, pp. 160085-160103, 2021.

W. Albattah, M. Nawaz, A. Javed, M. Masood, and S. Albahli, “A novel deep learning method for detection and classification of plant diseases”, *Complex & Intelligent Systems*, Vol. 8, No. 1, pp. 507-524, 2022.

LWDCD2020 dataset Source: <https://medium.com/analytics-vidhya/wheat-disease-detection-using-keras-48ae78990502>.